RATE-OF-CHANGE ANALYSIS APPLIED TO MACHINE TOOL MONITORING AND MAINTENANCE SCHEDULES

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In high-value manufacturing, production equipment is often calibrated on a regular basis to ensure it remains within the required absolute tolerance. However, this go/no go approach means that data relating to the rate of change of the condition of the asset is often lost or overlooked. This data can provide valuable insight into the current state of the machine, and provide estimates of when maintenance will be required to maintain the present level of performance. Analyzing the rate of decay of certain machine capabilities can assist with optimisation of maintenance schedules, allow the cost of replacement parts to be reduced or spread out, and give more reliable estimates of machine availability. The reasons for the loss of this data and a proposed design of a system to capture it are discussed here.

1. Introduction

The overall goal of machine tool manufacturers and maintenance teams has been described in the past by Mallet (1), essentially, as follows: Once a machine has been brought to a state where it is capable of producing parts to the specified tolerances, it will remain in that state for as long as possible. As discussed by Lawrence Mann Jr. et. al.(2), there are two approaches to this:Statistical based and Condition based.

Statistics based maintenance involves replacing components before calculations estimate that they should be beginning to fail. This is based on OEM's mean time to failure (MTTF) estimates. This process relies on careful calculation of wear curves related to the current machine processes and speeds. An alteration to any part of the process requires re-calculation of these figures.

Condition based monitoring of machine tools takes the approach that the degree of degradation of a component or machine can be measured and that this should dictate when restorative action is required. This is not a new idea, it has been discussed, tested and implemented, to varying degrees, since the early 1990s at least(2). Classic examples of condition based wear monitoring for specific parts are activities such as fluid analysis and vibration monitoring which look at changes in particle content of fluids, or examine the vibration spectrum of a particular machine as certain components degrade over time(3).

Although these techniques can indeed indicate when a gearbox is becoming worn, or if a bearings race has become chipped, they are not designed specifically to guarantee a go/no-go answer to the question of "can I cut a part successfully", especially in terms of accuracy degradation.

2. Current Industry Practice

An existing standard method of control is using statistical analysis of the results of parts produced on the machine having been measured on a coordinate measuring machine (CMM). If the data highlights that the critical features have drifted outside tolerance maintenance are tasked with investigating what has caused the defects, and correcting the machine accordingly. This process is illustrated in Figure 1 below.

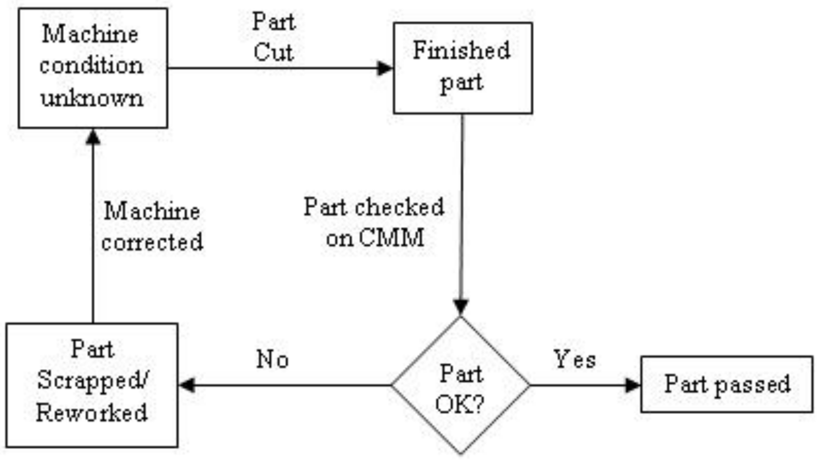

Figure 1: Existing Production/Verification Cycle

The downside to this method is that it measures defects in the manufactured part - if you are producing artefacts with a high capital value, or that are the product of months of sequential processing stages, this is an extremely costly and time-consuming method of defect identification.
Alternatively, if changes in the important machine outputs can be measured directly, prior to any actual cutting tasks, and these results efficiently stored and analysed, major cost and time savings could be realised.

Despite this, preventative condition-based maintenance is not used in every machine shop worldwide. Factors contributing to the low uptake of systems like this are things such as the cost of new metrology equipment (and the training that is required to use it effectively), ongoing personnel costs required for measurement and supervision and the lack suitable data storage and analysis expertise.

3. Avoiding Failure

The importance of recording the variations of a measured aspect of a machine tools metrology as it changes over time has not been ignored, and certain metrology systems provide the functionality to do this. For example, Renishaw's QC-20w Ballbar system(4) can display a "history" graph to show the values of various parameters contributing to non-circularity at each measurement occasion. However, the tolerance remains an absolute check so experience is required to interpret the history data.

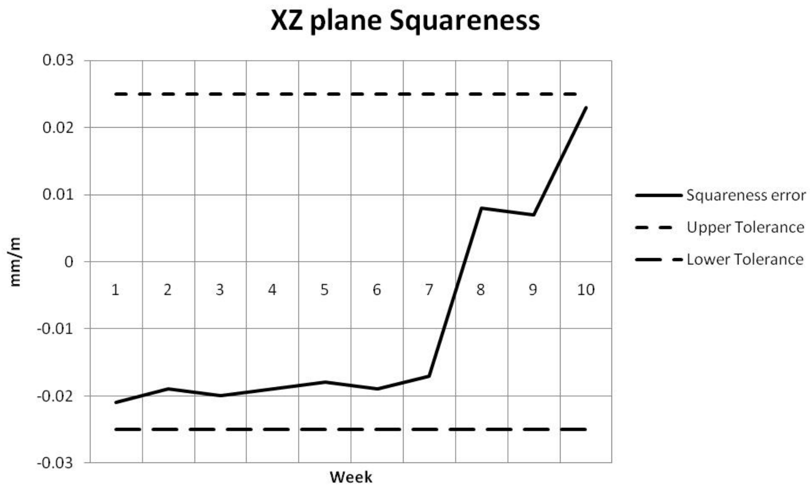

Figure 2: Rate of change example

In order to make predictions about the future, analysis of the rate of change of the measured errors is required. As shown in Figure 2, the recorded error is still within the upper tolerance limit (+/-0.025 mm/m in this case) and without direct analysis of the data, would appear acceptable. As should be evident from the chart however, it has climbed from a nominal value to a level only just inside the tolerance bounds in one measurement interval. Although this shows that the machine will produce a good part this time, this is a strong indicator that something is wrong within the machine's systems and might require intervention in the near future.

By calculating the rate of change of the error (E) over time (t) a tolerance (RC^{max}) can be assigned to it, so that we are alerted if these bounds are exceeded (Equation 2).

$$\Delta E = \frac{dE}{dt}$$ Equation 1

$$0 \leq \frac{dE}{dt} \leq |RC^{max}|$$ Equation 2

Where *dE* is in microns and *dt* is, in this case, in weeks.

It should be possible, by measuring the degradation of the machine's condition after each cutting process, or each batch of parts, to estimate how many times the cutting process can be performed before loss of accuracy will become a problem and maintenance will be required. Whilst in practice "measure each time" may not be possible due to the time needed to carry out all the required tests, even a less frequent calibrations schedule should be able to provide sufficient information to allow the creation of maintenance and calibration schedules that are more tailored to the present needs than a one-size-fits-all, yearly cycle.

The maximum maintenance interval (MMI) for the machine feature being measured can be described by:

$$MMI \leq \frac{Tol^{max} - E(t)}{\Delta E}$$ Equation 3

Where E(t) is the measured error at time t, and Tol^{max} is the maximum value at which the accuracy of the machine is guaranteed.

Although this is a relatively crude approach, it is more suitable to predict imminent machine failure than applying an average of the time to fail to this problem which can not be assumed to have Gaussian distribution.

4. Closed loop system

By adding a measurement step to the system, prior to the cutting process, problems can be identified before they are turned into defective parts, increasing the efficiency and, ideally, availability of the machine. This reduces the machining process to the cycle shown here in Figure 3.

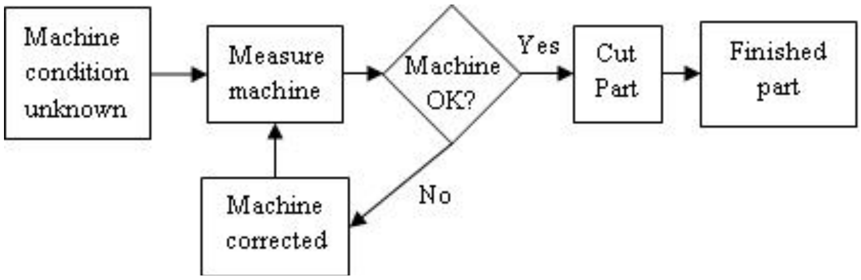

Figure 3: Closed loop system

5. Conclusions

The process of applying the rate of change tolerance to the directly recorded machine data can provide a good early warning system to alert maintenance to any rapidly degrading functions. It can also provide evidence based "loss of accuracy" timescales to aid in the creation of maintenance schedules.

Although not as easy to interpret the root-cause, the same methods could be applied to the data recorded from the CMM to provide indirect measurements of the machine tool's drift.

Future aims are to improve the robustness of the predictions produced by the software to include polynomial curve fitting, thus allowing more trends in the machine's deviations to be uncovered.

6. Bibliography

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